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Effect of Sensing Time Variation on Detection, Misdetection and False Alarm Probabilities in Cognitive Radio-Based Wireless Sensor Networks

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Abstract – *In this paper, we present an analytical derivation of the probability of detection, probability of misdetection and probability of false alarm in cognitive radio-based wireless sensor networks under a varying effect of sensing time. Sensing time is one of the most important parameters in cognitive radio-based networks. Particularly, in cognitive radio-based wireless sensor networks, the duration of channel sensing greatly impacts on probabilities of false alarm, misdetection and detection of primary user signal in a channel under investigation. In our analytical method, we have considered event that a given channel will be ON or OFF with different probabilities of ON and OFF states of the channel. From our simulation results, we found that, for different probability of ON channel state, there is significant change in probability of detection and misdetection as the sensing time increases. Simulation results also showed that for different probability of OFF channel state, probability of false alarm varies with sensing time.*

Keywords: *Detection, Channel, Misdetection, Sensing-Time, False-Alarm*

Nomenclature

W	Channel Sampling Frequency
T	Slot duration
λ_d	Detection Threshold
λ_f	False-Alarm Threshold
R	Data rate
t_1	Sensing slot
t_2	Transmission slot
C	Channel
H_1	Hypothesis PU available
H_2	Hypothesis PU absent
$i(t)$	Input signal
$i_f(t)$	Filtered signal
$[\ ]^2$	Squaring signal
$[\int]$	Integrator
$o(t)$	Output signal
$n(t)$	Noise signal
p	Channel ON duration
q	Channel OFF duration
P_d	Detection probability
P_f	False-alarm probability
P_m	Misdetection probability
Q	Q-function
SS_{eff}	Sensing efficiency
P_{ON}	Probability of Channel busy
P_{OFF}	Probability of channel free
L	Packet Size
$P_{success}$	Success probability
$P_{failure}$	Failure probability
σ_n^2	Noise Variance
σ_s^2	PU signal variance
P_1	Channel detection probability
P_2	Misdetection probability
P_3	Collision probability
P_4	False-alarm probability
P_5	Channel available probability

I. Introduction

There has been increase in research work in the field of wireless sensor networks (WSN) in recent time. This is due to many applications of sensor networks. Among others, disaster relief applications, battle-field surveillance, environment monitoring and biodiversity mapping, intelligent health care and medicine, facility management, intelligent building, telematics, and remote underwater surveillance are examples of WSN applications. WSN operate in the industrial scientific and medical (ISM) frequency band. 2.4GHz ISM band is unlicensed band that is open to other applications such as, IEEE 802.11 systems, IEEE 802.15.4 WPAN, wireless microphones, Bluetooth and microwave oven.

As a result of numerous applications and devices operating in this band, there is spectrum overcrowding problem. This leads to interference among dissimilar wireless applications using this band. In some locations, the allocation of the 2.4GHz frequency band has reached all-time height of 90% according to [1].

Due to spectrum scarcity and interference in the licensed and unlicensed band, a new efficient spectrum utilization paradigm has been proposed.

This paradigm is called cognitive radio (CR). Cognitive radio idea makes it possible for communication devices to adaptively and dynamically utilize the limited spectrum channels in an opportunistic manner.

Cognitive radio-based sensor networks (CRWSN) have the capability to sense its radio environment, intelligently adapt its communication parameters and reconfigure them accordingly. This unique feature of CR provides an avenue for solving the spectrum scarcity problem confronting wireless communication within the licensed and unlicensed frequency bands. As a result of the numerous potential advantages derivable from CR deployment, few authors have proposed a new sensor network called CRWSN.

This type of sensor network combines the CR functionalities with the traditional WSN to give a more robust sensor network. It is possible for this sensor networks to operate in both the licensed and unlicensed band in an opportunistic manner by sensing the spectrum for available channel. This is called opportunistic spectrum access (OSA). This is the core of cognitive radio technology. The new CRWSN networks prove to be more challenging than the traditional wireless sensor networks because CRWSN combines the features of WSN and CR in one system. Among other challenges are energy consumption and processing constraints.

The CRWSNs are also deployed in remote locations and they are low-power-battery-driven systems. In many cases, battery recharge is not possible. As a result of miniaturization of sensor nodes, computation complexity has to be kept simple.

In addition to these problems, simple antennas and radios are to be used in order to mitigate the problem of cost and affordability. Our focus in this paper is on the effect of spectrum sensing time on the detection, misdetection and false alarm probabilities during spectrum sensing in CRWSN.

II. Related Works

In [1], the authors presented recent developments and open research issues in spectrum management based on CR networks. Specifically, the work focused on the development of CR networks that does not require modification of existing networks. This work failed to address the issue of coexistence and interference between the primary user signal and that of secondary user CRWSN. CRWSN is a resource-constrained network. It is therefore very important to develop a suitable spectrum sensing technique that will optimize the limited channel resources of the network. In view of this need, the authors in [2] proposed energy detection-based spectrum sensing for cognitive radio network. The authors majorly focused on theoretical analysis based on the work done previously in [3].

The authors in [4] did a survey work on spectrum management in cognitive radio network, and they came up with four major open research questions about spectrum sensing, spectrum decision, and spectrum sharing and spectrum mobility.

However, in furtherance to this work, authors in [5] proposed optimal spectrum sensing for cognitive radio network. On their part, authors in [6] proposed a scheme for channel access in cognitive radio sensor network with specific focus on energy efficiency.

In [7], the authors tried to answer the question of how frequently should spectrum sensing be carried out. The authors came up with trade-off between throughput and collision based on the effect of sensing time and PU activity pattern within the channel.

In a similar manner to the work done in [6], authors in [8] focused on energy efficiency as they considered spectrum sensing and access in cognitive radio networks.

In their work, they proposed optimal spectrum sensing and access mechanism using energy cost as their objective function. However, their work does not apply to CRWSN. The authors in [9] were concerned majorly with the order of sensing in a multi-channel cognitive radio network. They applied the principle of optimal stopping rule to decide when to stop sensing operation.

It is well known that sensing time is a major factor in spectrum sensing operation. Authors in [10] attempted using soft decision scheme to optimize the sensing time based on other parameters in a cooperative cognitive radio network.

The outcome of their work shows that optimal sensing time decreases with increase in signal to noise ratio. Authors in [11] looked at the challenges and solutions to spectrum sensing in cognitive radio network. This is a review work that described various spectrum sensing approaches available in literatures. Work in [12] directly focused on cognitive radio wireless sensor with specific thrust in the mode of channel selection for the cognitive radio sensor network secondary user.

Weighted combining cooperative energy detection spectrum sensing was used for dynamic spectrum access in [13]. Comparing their approach to equal gain and hard decision combining, they showed that weighted combining approach provided a better improvement. In addition, authors in [16] proposed optimal fuzzy fusion scheme to improve performance and reduce complexity of cognitive radio systems. A new reinforcement learning approach called DAC-PS is developed for solving the problem of an autonomous mobile robot navigating in an unknown and dynamic environment in [17].

From various works available in literature, we observed to the best of our knowledge that non have considered the effect of the probabilities of ON and OFF activities of primary user to determine how sensing time affects probabilities of detection, misdetection and false alarm in a CRWSN.

This is our focus in this work. The justification for this however is, for different probability of ON state of the channel, we will have different sensing time. This also determines what the detection, misdetection and false alarm probabilities will be. The rest of this paper is organized as follows; section III described the network model. In section IV, we did the analysis of the various probabilities, while in section V we analyse the behaviour of the various channel states.

Section VI shows the simulation and result discussion. Finally, section VII gives the conclusion.

III. Network Model

Fig. 1 illustrates a simple cognitive radio network scenario. This network comprises of PU network and SU network operating within the same spectrum band in an overlay manner. The PU is the licensed user of the communication channel. The secondary user uses the licensed channel in an opportunistic manner when the primary user activity is not detected within the channel at a given period of time.

Cognitive radio is one critical enabling technology for future communications and networking that will bring about a more efficient and flexible way of utilizing the limited network resources. In cognitive radio based communication systems, the radio devices can adapt their operating parameters such as, transmission power, frequency, and modulation dynamically to the surrounding radio environment. This differentiates it from the traditional communication systems in which spectrum utilization is based on fixed spectrum allocation.

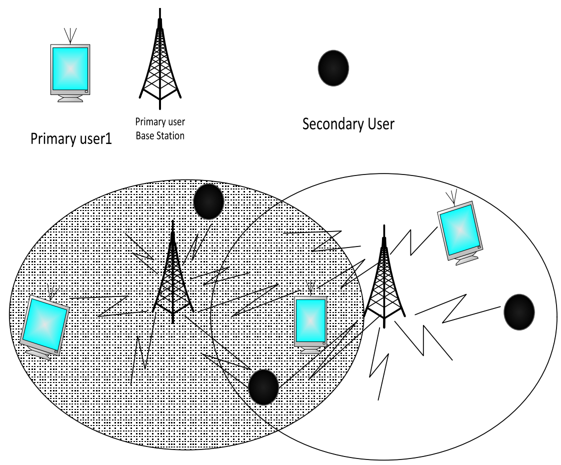

Fig. 1. Cognitive radio network scenario

III.1. *Cognitive Radio-based Wireless Sensor Network Model*

We considered a cluster-based cognitive radio-based wireless sensor network made up of cluster heads (CH), and member nodes (MN). The nodes are assumed to be static.

This is illustrated in Fig. 2. Cluster heads are full functioning device (FFD) with cognitive radio capabilities, while the member nodes are reduced functioning devices (RFD) which only send their captured data to the CH through sensed available channel. The CH coordinates communication within the network.

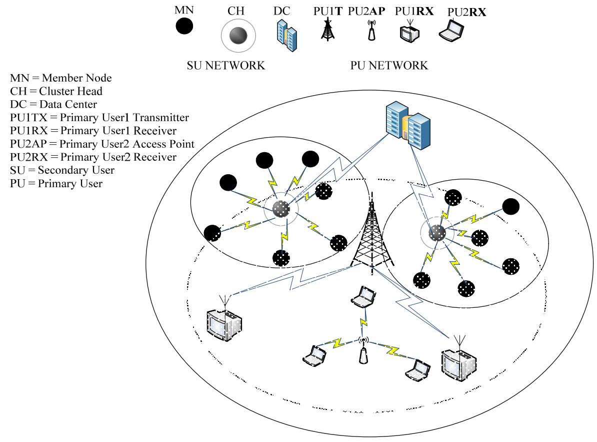

Fig. 2. Network model of cluster-based cognitive radio-based wireless sensor networks

III.2. *Cognitive Radio-based Wireless Sensor Networks Channel Access Model*

Timing pattern of the sensor network is shown in Fig. 3. This is a time-slotted scheme that is divided into sensing and transmission slots respectively. During the sensing slot, the CH scans the primary user (PU) spectrum for any available channel for communication by the sensor network.

Depending on the sensing out, the CH decides whether to transmit or to sense another channel. When a channel is found available and possesses good communication condition depending on the quality of service requirements of the application-specific CRWSN, the CRWSN switch into transmission time slot. During the transmission time slot, packet transmission between the member nodes and the CH takes place for a transmission time that is less than or equal to the entire transmission slot duration.

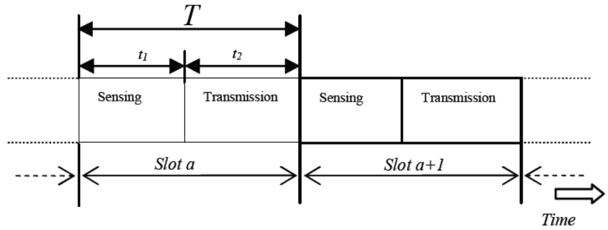

Fig. 3. Channel access timing framework

Time t_1 and t_2 represents the slot durations for sensing and transmission respectively. The higher the sensing duration, the more accurate the sensing outcome is expected to be. However, channel sensing is energy consuming. Also, in order to ensure accurate packet transmission, duration for transmission should be kept sufficiently large enough to accommodate the entire data packet size. Excessively high transmission time can be unbeneficial to the CRWSN in the event that PU begins transmission suddenly during the transmission slot.

Therefore, there is a trade-off between increasing sensing time and transmission time.

This also results in trade-off between sensing time and throughput. Accurate probability of detection and high spectrum sensing efficiency in terms of near zero misdetection probability are two important aims of spectrum sensing described in our work.

In Fig. 4, we show our channel access scheme designed for CRWSN. This is a time-slotted scheme based on the PU behavior in any particular channel of interest. Each frame is divided into two time slots which are, sensing and transmission slots as mentioned above.

Channel sensing and transmission is done based on time framework shown in Fig. 3. The local common control channel (LCCC) is introduced in the access schemed for the purpose of information control. For each cluster, there are *C* channels and a LCCC. A channel is considered available when there is no PU activity in the channel during sensing operation, and channel condition is suitable for data transmission by the secondary user (SU) CRWSN. Whatever be the outcome of the sensing operation by the CH of the CRWSN, the CRWSN proceeds to one of the following, transmit-receive state or switching state. Fig. 4 clearly depicts how this operation takes place.

As a result of radio frequency (RF) front-end hardware limitation and energy constrain of sensor networks, energy detection spectrum sensing is considered. With energy detection spectrum sensing technique, prior knowledge of the PU activity is not known by the SU CRWSN. Hence, the CH does not have to keep statistical record of the PU activity which is random in nature.

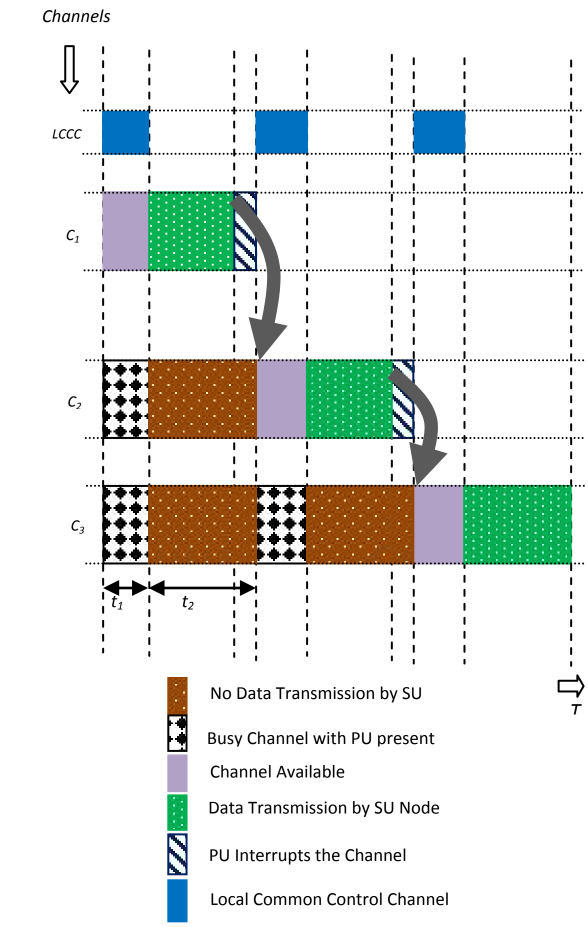

Fig. 4. Sensing, channel access and switching operations of cognitive radio-based wireless sensor networks

III.3. Energy Detection Spectrum Sensing Process

This is a spectrum sensing technique that makes use of the received signal at the CR receiver to determine the presence of the primary user within the channel. This process can be carried out both in the time and frequency domain.

With reference to [3] and [14], the energy detector consists of band-pass filter, which pre-filters the noise bandwidth, the squaring device and an integrator. Fig. 5 shows the block diagram of energy detection process in time domain.

Energy detection spectrum sensing technique is a test of two hypothesis based on the primary user activity in the channel. Hypothesis H_0 signifies the event that primary user signal is not available in the channel. Under this condition, the CRWSN only detects noise signal.

Hypothesis H_1 signifies the event that the primary user signal is available in the channel. Hence, the CRWSN detects both the primary user signal in addition to noise signal:

$$\begin{cases} H_0 : \quad o(t) = n(t) \\ H_1 : o(t) = i(t) + n(t) \end{cases} \tag{1}$$

From (1), o(t) is the received output of the integrator which decides if the channel is available or not available.

For H_0, the received output is only noise sample $n(t)$.

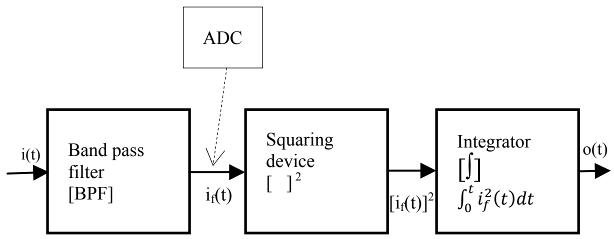

Fig. 5. Block diagram of energy detection process

We assume additive white Gaussian noise (AWGN) with zero average and σ_n^2 variance. For H_1, received output is addition of sampled primary user signal i(t) with σ_s^2 variance and AWGN noise. The test decision criterion of energy detection is given as:

$$o(t) = \int_0^{t_1} i_f^2(t)dt \tag{2}$$

III.4. Primary User Behavior Model

PU behavior is modeled as a two-state, time-homogenous discrete Markov process Wang et al (2012).

This is a preferred model because of the inter-dependence between the present state and the previous state.

The two-state Markov process is shown in Fig. 6. We considered a spectrum band consisting of C channels, each having different bandwidth BW. The PU can either be occupying the channel, which means, the channel is in ON state with PU signal present (that is, channel busy), or PU signal is absent, which means PU is in OFF state and the channel is available (that is, channel available) at any given time. When the PU occupies a channel, the channel is not available for the CR user to transmit.

Otherwise, the CR user transmit within the available channel assuming that other channel conditions such as fading and noise effects are favourable for packet transmission.

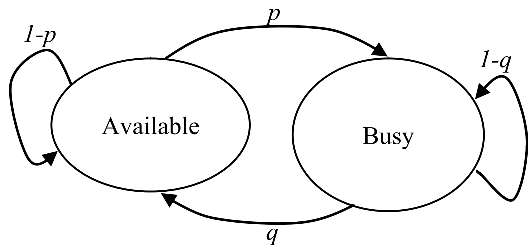

Fig. 6. Two state Markov model for primary user channel behavior

The PU occupancy of the channel follows independently identically distributed (i.i.d) exponential random variables p and q representing duration of ON and OFF respectively. Similarly, based on our previous work in [15], probabilities of ON and OFF are derived as follows:

$$P_{ON} = \frac{p}{p+q} \tag{3}$$

$$P_{OFF} = \frac{q}{p+q}(4) \tag{4}$$

IV. Analysis of Detection, Misdetection and False-alarm Probabilities

From energy detection spectrum sensing described above, there are three important detection performance metrics which are, probability of detection P_d, probability of false alarm P_f, and probability of misdetection P_m. Detection probability is the probability that PU signal is correctly detected to be present in the channel within a sensing time. Probability of false alarm is the probability that reports the channel being occupied by the PU while the PU is actually absent at the instant of sensing the channel. Misdetection probability is also a probability that depicts the channel sensing outcome as free of PU signal while in actual sense; the PU is active in the channel during the sensing period. Generally, in terms of the hypothesis in (1), we define these probabilities mathematically define as:

$$\begin{cases} P_d = P_r\{decision = H_1|H_1\} \\ P_f = P_r\{decision = H_1|H_0\} \\ P_m = P_r\{decision = H_0|H_1\} \end{cases} \tag{5}$$

where:

$$P_m = 1 - P_d \tag{6}$$

For a given detection and false alarm decision thresholds λ_d and λ_f respectively, probabilities of detection and false alarm from (5) can be written as:

$$P_d = P_r\{o(t) > \lambda_d|H_1\} = Q\left(\frac{\lambda_d - 2t_I W(\sigma_s^2 + \sigma_n^2)}{\sqrt{4t_I W(\sigma_s^4 + \sigma_n^4)}}\right) \tag{7}$$

$$P_f = P_r\{o(t) > \lambda_f|H_0\} = Q\left(\frac{\lambda_f - 2t_I W\sigma_n^2}{\sqrt{4t_I W\sigma_n^4}}\right) \tag{8}$$

$$o(t) > \lambda_d \; decides \; PU \; signal \; is \; ON$$

$$o(t) < \lambda_f \; decides \; PU \; signal \; is \; OFF$$

$$Q = \frac{1}{\sqrt{2\pi}}\int_x^\infty exp\left(-\frac{u^2}{2}\right)du$$

where λ_d and λ_f are the detection and false alarm decision threshold values respectively, σ_n^2 and σ_s^2 are noise and primary signal variances, W is the sampling frequency, and t_I is the sensing time of the SU. Q is the tail probability of the standard normal distribution or the probability that a normal (Gaussian) random variable will obtain a value larger than x standard deviations above the mean. It is formally called Q-function. From (3), (4), (7) and (8), we can formulate the P_d and P_f as a function of sensing time, ON and OFF event probabilities as:

$$P_d(t_I) = \left(\frac{p}{p+q}\right)Q\left(\frac{\lambda_d - 2t_I W(\sigma_s^2 + \sigma_n^2)}{\sqrt{4t_I W(\sigma_s^4 + \sigma_n^4)}}\right) \tag{9}$$

$$P_f(t_I) = \left(\frac{q}{p+q}\right)Q\left(\frac{\lambda_f - 2t_I W\sigma_n^2}{\sqrt{4t_I W\sigma_n^4}}\right) \tag{10}$$

Accurate probability of detection and high spectrum sensing efficiency in terms of near zero misdetection probability are two important aims of spectrum sensing.

Therefore, sensing efficiency is defined as the ratio of the transmission time to the total CR operation time.

From Fig. 3 we determine the spectrum sensing efficiency SS_{eff} as:

$$SS_{eff} = \frac{t_2}{t_1 + t_2} \tag{11}$$

where, t_1 and t_2 corresponds to sensing and transmission time slots respectively.

V. Channel State Probabilities Analysis

Five channel states were considered. These states are detection, misdetection, false alarm, collision and success states. We describe each state as shown in Fig. 7.

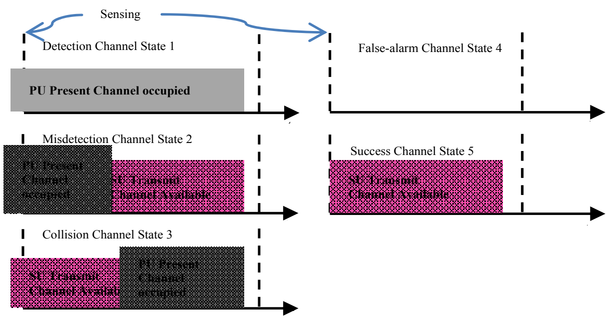

Fig. 7. Channel States for CRWSN under Dynamic Spectrum Access

There are two possible outcomes of sensing by the SU if the PU signal is present in the channel. It is either the PU is detected or is mis-detected. It therefore implies that, the probability that the PU is ON, which means, the probability that the channel is busy with PU activity is the summation of the probability of detection and of misdetection.

The PU must actually be occupying the channel in the event of these two states. As shown in Fig. 7, let P_1, P_2, P_3, P_4, P_5 represent the probability of each channel state accordingly.

Therefore, the probability of ON state can be written as:

$$P_{ON} = P_1 + P_2 \tag{12}$$

Substituting for P_{ON} in (9), then we solve for P_2, where P_2 is the same as the probability of misdetection state, we have:

$$P_m(t_I) = P_{ON} Q\left(\frac{2t_I W(\sigma_s^2 + \sigma_n^2) - \lambda}{\sqrt{4t_I W(\sigma_s^4 + \sigma_n^4)}}\right) \tag{13}$$

A channel will only be in OFF state when the PU signal is not available in the channel as at the time of sensing by the SU. From Fig. 7, this only occurs in states 3 to 5. Therefore, probability of OFF channel state is the summation of the probabilities of states 3, 4 and 5, which are denoted as P_3, P_4 and P_5:

$$P_{OFF} = P_3 + P_4 + P_5 \tag{14}$$

P_4 is the same as the probability of false alarm. This has been determined in (10) as $P_f(t)$. P_4 and P_5 are dependent on the packet size, L being transmitted by the SU. At every decision instant, the number of available channels is calculated as CP_{OFF} by the SU, where C is the number of channels. Based on [7], transmit-receive time t_2 as shown in Figure 3 is given as $t_2 = {}^{L}/_{R}$. Where L is the packet size and R is data rate for the SU transmission. If the probability of channel failure is given as $P_{failure} = 1 - e^{-\frac{L}{Rp}}$ and the probability of success is given as $P_{success} = e^{-\frac{L}{Rq}}$, the probability of P_4 and P_5 can be determined as follows:

$$P_4(L) = 1 - e^{-\frac{L}{Rp}}(P_{OFF} - P_3) \tag{15}$$

$$P_5(L) = e^{-\frac{L}{Rq}}(P_{OFF} - P_3) \tag{16}$$

VI. Simulations and Results

Channel access in cognitive radio-based wireless sensor networks depends on the following parameters to determine their efficiency. These performance metrics are, probability of detection, probability of misdetection, and false alarm probability as a function of sensing duration. We used MATLAB to carry out simulations and we obtained unique results of the relationships that exist between each of the probability and sensing time under different probability of channel busy and available.

Our simulation parameter set is shown in Table I.

TABLE I
SET OF SIMULATION PARAMETERS

Parameter	Description	Value
BW	Channel Bandwidth	1MHz
ISM-Band	Operating frequency Band	2.4GHz
λ	Energy Detection Threshold	5
d_{SU-PU}	Distance between PU and SU	50m
R	Data rate	40kbps
δ	Path loss component	2.5
P_{ON}	Probability of Channel busy	0.8, 0.5, 0.25, 0.1
P_{OFF}	Probability of channel free	0.2, 0.5, 0.75, 0.9
N_o	Noise Power	1.38×10^{-22}
PU_p	PU Transmission Power	10dB
I_m	Maximum Interference Ratio	0.1
σ_n^2	Noise Variance	1
σ_s^2	PU signal variance	1

In Fig. 8, the variation of sensing time and the probability of detection is shown under a varying ON state probabilities. For different Pr_{ON}, there is a similar trend in the relationship between the sensing time and probability of detection. The result shows that, as the sensing time increases, there is an initial sharp rise in the probability of detection. This sharp rise is particularly noticeable at Pr_{ON}=0.8, 0.5 and 0.25. However, beyond 0.4μs sensing time, there is a descent in the sharpness of increase in probability of detection. This is so because of finite sensing slot duration.

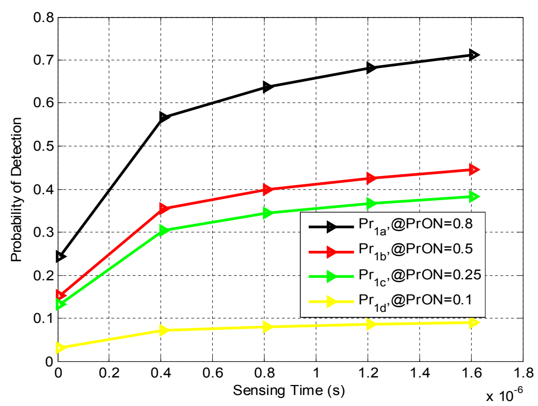

Fig. 8. Variation of probability of detection with sensing time under varying Pr_{ON}

Fig. 9 shows the variation of sensing time with the probability of misdetection state. Misdetection occurs when the SU cognitive radio sensor network could not detect the presence of a primary user in the channel even though the PU signal is still present within the channel.

The sensing time has significant effect on the probability of misdetection within the sensing slot of the SU frame. There is sharp decrease in the probability of misdetection with increase in sensing time.

This is logical because when the sensing time increases, it creates better chances for the detection of PU signal within the channel and definitely reduces the chances of misdetection. As expected, this sharp decrease is witness at higher values of Pr_{ON}.

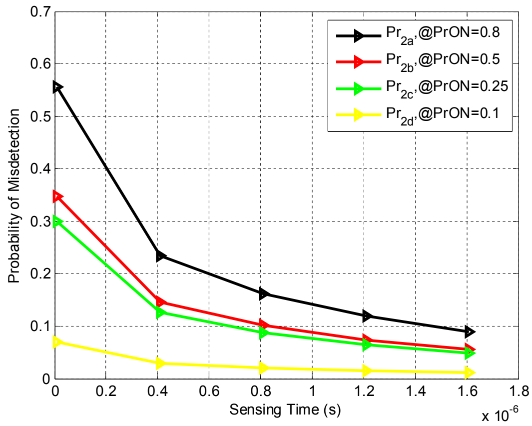

Fig. 9. Variation of probability of misdetection with sensing time under varying Pr_{ON}

From Fig. 10, it could be seen that the probability of false alarm, which is a situation in which the CR CH report to other MNs the outcome of its sensing that the PU signal is present in the channel, whereas the PU is not occupying the channel. This is understandable from the learning of the SUs. Based on the learning outcome of the past, the probability of false alarm tends to vary as the sensing time changes. This will ultimately reduce the reward rate of channel access by the SU. It could be seen from Fig. 10 also that as the Pr_{OFF} state increases, the increase in probability of false alarm witnessed is sharp.

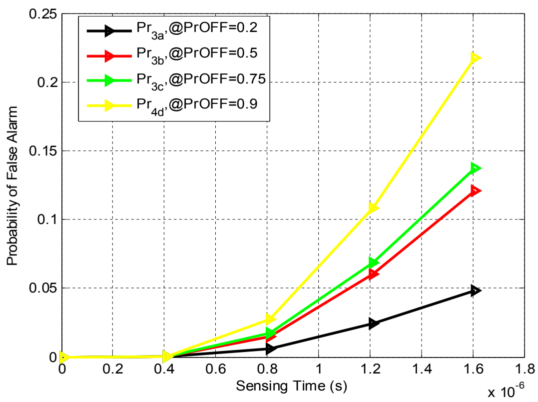

Fig. 10. Variation of probability of false alarm with sensing time under different Pr_{OFF}

VII. Conclusion

In this paper, we have presented an analytical derivation of the probability of detection, probability of misdetection and probability of false-alarm in CRWSN under varying probability of ON and OFF states of channel. We have shown how sensing time affects these parameters.

From simulation results, we found that; for different probability of ON channel state, there is significant variation in the probability of detection and misdetection respectively as the sensing time also changes. Simulation results also showed that for different probability of OFF channel state, probability of false alarm varies with sensing time.

In this work, we have limited our consideration to sensing duration. However, for future work, we will consider transmission time slot. As a form of limitation, this analytical approach is applied specifically to cognitive radio-based wireless sensor networks. This may not be applicable to other type of networks. Hence, our analytical approach is not generic.

Acknowledgements

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